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Optimum estimation and forecasting of renewable energy consumption by artificial neural networks

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ABSTRACT

Increasing energy consumption has led to release of pollutants such as greenhouse gases that affects on human health, agriculture, natural ecosystems, and earth temperature. Accurate estimation and forecasting of renewable energy is vital for policy and decision-making process in energy sector. This paper presents an Artificial Neural Network (ANN) approach for optimum estimation and forecasting of renewable energy consumption by considering environmental and economical factors. The ANN trains and tests data with Multi Layer Perceptron (MLP) approach which has the lowest mean absolute percentage error (MAPE). The proposed approach is particularly useful for locations where there are no available measurement equipments. To show the applicability and superiority of the proposed ANN approach, monthly available data were collected for 11 years (1996–2006) in Iran. Complete sensitivity analysis is conducted to choose the best model for prediction of renewable energy consumption. The acquired results have shown high accuracy of about 99.9%. The results of the proposed model have been compared with conventional and fuzzy regression models to show its advantages and superiority. The outcome of this paper provides policymakers with an efficient tool for optimum prediction of renewable energy consumption. This study bypasses previous studies with respect to several distinct features.

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1. Motivations and significance

Renewable energy as the energy that is replenished naturally has a crucial role in environment protection, decreasing earth temperature, ozone layer protection and sustainable development. Additionally, fossil fuel resources with themselves bring harmful

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impacts on health and environment. Moreover, they are being replaced with new and clean sources of energy. Therefore, the need for clean and safe energy is essential in long term. Long-term planning to increase renewable energy consumption is needed to recognize the amount of renewable energy consumption in different periods and specify the important factors affecting on renewable energy demand. Thus, optimum forecasting of renewable energy consumption is vital. By exploring in the renewable energy literature we find that the measurement of renewable energy consumption has a costly procedure and also the required measurement instruments are not easily available. Thus, an accurate and efficient method for prediction of renewable energy consumption can be very helpful in this perspective. An intelligent approach is proposed to forecast and predict renewable energy consumption by an effective and efficient procedure.

2. Introduction

As populations grow, many faster than the average 2%, the need for more and more energy is exacerbated. Enhanced lifestyle and energy demand rise together and the wealthy industrialized economies which contain 25% of the world's population consume 75% of the world's energy supply [1]. Renewable energy sources are readily available in nature. Increasing atmospheric concentrations of greenhouse gasses increase the amount of heat trapped (or decrease the heat radiated from the earth's surface), thereby raising the surface temperature of the earth [2]. There are many alternative new and renewable energy sources which can be used instead of harmful fossil and conventional fuels. The energy resources have been split into three categories: fossil fuels, renewable resources, and nuclear resources [3]. The optimum decision as to what types of energy source should be utilized must, in each case, be made on the basis of economic, social, environmental and safety considerations. Exploring the literature in the field of energy consumption shows that in several countries there is a positive relationship between gross domestic production (GDP) and energy consumption. Sadorsky [4] shows that a 1% increase in real GDP per person increases per capital renewable energy consumption by 8.44% while a 1% increase in carbon dioxide emissions per person increases per capital renewable energy consumption by 5.23%. Improving some of the main features of manufacturing technology is directly related to energy consumption. The importance of energy in economic development is recognized universally and historical data verify that there is a strong relationship between the availability of energy and economic activity [2]. Increasing in greenhouse gases levels in the atmosphere will lead to warmer temperatures on the earth's surface. CO_2 is main greenhouse gas associated with global warning. At the present time, coal is responsible for 30–40% of world CO_2 emissions from fossil fuels. About 98% of carbon emissions result from fossil fuels (coal, oil, and natural gas) combustion and also currently, renewable energy resources supply 14% of the total world energy demand [5]. In addition, Demirbas [5] stated that accumulation of greenhouses in atmosphere leads to negative impacts such as air pollution and acid rains. Air pollution can cause health problems and it can also damage the environment and property. It has caused thinning of the protective ozone layer of the atmosphere, which is leading to climate change and acid rain causes extensive damage to water, forest, soil resources and even human health. It is said that it can corrode buildings and be hazardous to human health.

The limitations of energy resources and strictly increasing energy consumption trend show the need to design accurate devices for consumption of energy in manufacturing sector in particular and industrial sector in general. Hence, there is a need to focus on trend of energy consumption in the future, particularly in manufacturing sector. The renewable energy resources (i.e., solar, wind, wave, biomass and geothermal energy) have shown undeniable benefits with regard to essential technical, environmental and political visions which can be considered as the future prospect of energy. Renewable energy is energy that comes from natural resources such as sunlight, wind, rain, tides, and geothermal heat, which are renewable (naturally replenished). Renewable energy is freely available and could be easily harnessed to reduce our reliance on hydrocarbon-based energy by both, passive and active designs. With expanding of energy consumption at worldwide, release of pollutants such as greenhouse gases makes that human health, agriculture, natural ecosystems be affected and also greenhouse gases traps the heats rising from earth and so makes increasing in earth temperature. One of the ways to decrease these harmful effects is developing of clean energies consumption such as renewable energy consumption. Using renewable energy and its impact in reducing greenhouse emission necessitates an exact estimation of renewable energy consumption. This subject is usually possible through measurement equipments of component of renewable energy (i.e., solar energy, windy energy, tidy energy and so on) while these devices are not available in some of remote or rural locations.

Using artificial neural network has proved its efficiency as an estimation tool for predicting factors through other input parameters which have no any specified relationship. Some examples of this work are provided in [6–12]. Also the capabilities of ANN methods help us to gain more reliable results. In this study we have introduced six most important effective parameters for forecasting renewable energy consumption by an integrated ANN model as follows: carbon dioxide emission, nitrogen oxide emission, carbon mono oxide emission, gas price, oil price and GDP. The output is monthly renewable energy consumption and also for post process model we considered lagged observation. Lagged variable leads to a stable ANN model. We have applied these input parameters in the framework of ANN model and data has been tested and trained by Multi Layer Perceptron (MLP). Comparing the acquired results of this study respect to well-known regression models and fuzzy regression prediction models shows a considerable improvement in the error amount and accuracy of prediction. Also the proposed model has shown higher accuracy with regard to other similar studies which use ANN methods. As an instance case study, we collected monthly data for 11 years (1996–2006) in Iran and then the best ANN model was chosen by sensitivity analysis process. In the present work, we provide a prediction with a believable amount of error which is obtained with regard to more available input parameters.

3. Studies on the advances in developing renewable energy and applied methods

The use of renewable energy offers a range of exceptional benefits, including: a decrease in external energy dependence; a boost to local and regional component manufacturing industries; promotion of regional engineering and consultancy services specializing in utilization of renewable energy; increased R&D, decrease in impact of electricity production and transformation; increase in the level of services for the rural population; creation of employment, etc. [13]. Interesting consequences can be obtained from the analysis of the trend of main world energy indicators between 1973 and 2004 [14]: (1) the rate of population growth is well below the GDP, resulting in a considerable rise of per capita personal income and global wealth, (2) primary energy consumption is growing at a higher rate than population, leading to the increase of its per capita value on 15.7% over the last 30 years, (3) CO_2 emissions have grown at a lower rate than energy

consumption showing a 5% increase during this period, (4) electrical energy consumption has drastically risen leading to a percentage increase in final energy consumption (18% in 2004), (5) efficiency in exploiting energy resources, shown as the relation between final and primary energy, has declined by 7% points, especially due to soaring electrical consumption, and (6) final and primary energy intensities have dropped because of the higher rate of growth of the GDP over the energy consumption increasing ratio, resulting in an overall improvement of the global energy efficiency. Llera et al. [15] developed an analytical model based on a value-chain approach for forecasting job creation from renewable energy development in order to address the socioeconomic impacts of renewable energy developments. They mentioned that job creation is increased along with developing renewable energy systems. Singh [16] reports that renewable energy sources produce between 1.7 and 14.7 times more jobs than natural gas sources and up to 4 times more jobs than coal plants in the same conditions. Moreno and López [17] studied the effect of renewable energy on employment and show that the installation, operation and maintenance of different renewable energy systems, makes the emergent professional profiles and required skills related to the new jobs.

Lund [18] addressed three technological ways including efficiency improvements in energy production, energy savings on the end-uses, and strategies, and the substitution of fossil fuels with various sources of renewable energy in order to analyze the different strategies for sustainable development of renewable energy. Pehnt [19] presented a dynamic approach for the Life Cycle Assessment (LCA) of renewable energy in order to assess the advantages of renewable energy respect to other energy sources. The outcome of this paper shows that renewable energy dominates other energy sources in terms of the inputs of finite energy resources and emissions of greenhouse gases. Unlike fossil fuels energy consumption that only increases economic growth, renewable energy consumption increases the genuine savings and economic development [20]. Al-mulali et al. [21] studied the bi-directional long run relationship between energy consumption, CO_2 emission, and economic growth in the Latin American and Caribbean countries. They indicated that although 60% of the considered countries have a positive bi-directional significant relationship between energy consumption, CO_2 emission, and economic growth, the others have mixed results. They finally propose the use of renewable energy in the considered countries to eliminate the unnecessary waste of energy. Wang et al. [22] stated that energy consumption, economic growth, and CO_2 emission are cointegrated. Chien and Hu [23] investigated the relationship between renewable energy and technical efficiency in developed and emerging economies and find that increase in renewable energy consumption will increase technical efficiency.

Carbon dioxide (CO_2) is one of the most foremost greenhouse gases in the atmosphere; the energy sector is dominated by the direct combustion of fuels, a process leading to large emissions of CO_2. CO_2 from energy represents about 60% of the anthropogenic greenhouse gas emissions of global emissions [24]. Dunn and Flavin [25] stated that CO_2, which is released into the atmosphere from the burning of fossil fuels, is the single most important greenhouse gas contributing to the “anthropogenic forcing of climate change” in the northern hemisphere, Thus, they concluded the share of CO_2 in warming is expected to rise from slightly more than half today to around 3/4th by 2100 and also stated that the average global surface temperature would be raised more during the 20th century than during any other century in the last 1000 years. Iniyan et al. [26] proposed Optimal Renewable Energy Mathematical (OREM) model and also they show that their model will facilitate the effective utilization of renewable energy sources over the years 2010–2011, 2015–2016 and 2020–2021. Habbane et al. [27] developed a modified solar radiation model to determine solar irradiance from sunshine hours for a number of stations located in hot dry arid climates. An optimization model has been developed by Suganthi and Williams [28] to determine the optimum allocation of renewable energy in various end-uses in India for the period 2020–2021, taking into account commercial energy requirement. Iniyan and Sumathy [29] presented an optimal renewable energy model (OREM) that minimizes the cost/efficiency ratio and determines the optimum allocation of different renewable energy sources for various end-uses and the potential of renewable energy sources, energy demand, reliability of renewable energy systems and their acceptance level have been used as constraints in the model. Danny Harvey [30] estimated the impact on atmospheric CO_2 emission-reduction strategies, using the coupled climate–carbon cycle model. Celiktas and Kocar [31] evaluated Turkey′s renewable energy future by using the Delphi method.

Banos et al. [32] mentioned that although renewable energy development has many advantages, the need to complex optimization method is necessary in this field due to discontinuous generation resulted because of climate changes. Then, they gave a widespread review on the single and multi-objective optimization methods that use intelligent paradigms such as genetic algorithms, ANNs, differential evolution as well as mathematical modeling such as integer-linear programming methods, which are applied in different parts of renewable energy such as wind power, solar energy, hydropower, bioenergy, geothermal energy, and hybrid systems. Also, their review covers the method applied in design, planning and control of renewable energy systems. Another interesting review covering the models using optimization methods in energy sector is related to the work of Jebaraj and Iniyan [33]. Sadorsky [4] presented an empirical model of renewable energy consumption for the G7 countries and applied Panel cointegration for prediction. The main result of this study was that in the long term, increases in real GDP per capita and CO_2 per capita are found to be major drivers behind per capita renewable energy consumption. We have also considered these components in our study as well as other most important factors affecting renewable energy consumption.

Kalogirou [34] used artificial neural network technique for the estimation of heating-loads of buildings as well as for the prediction of energy consumption of a passive solar building. Multiple hidden layer architecture has been used in the modeling. Kalogirou [35] presented a comprehensive review about the successful applications of ANNs in renewable energy systems. This work studies different components of renewable energy systems including modeling of solar steam generator, solar radiation prediction, and wind speed prediction etc. Sozen et al. [36] implemented an efficient ANN model for forecasting solar resource in Turkey. The back-propagation learning algorithm is used in feed forward single hidden layers. They reported the efficiency of

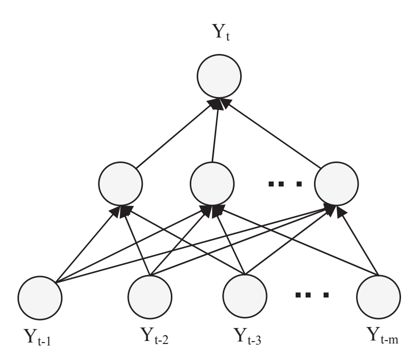

Fig. 1. A three-layer MLP network.

applied ANN respect to conventional regression models in forecasting of solar resources.

From the above surveyed relevant works in renewable energy, the importance of utilizing renewable energy, its significant benefits and also its crucial role in decreasing greenhouse gases emission and strategic planning is manifested. Therefore, accurate estimation and forecasting of renewable energy is vital for policy and decision-making process in energy sector. This paper develops an efficient ANN model that able to estimate and forecast renewable energy consumption in an optimum way considering effective input variables described in previous Section.

4. Method: Integrated ANN

In general, ANNs are simply mathematical techniques designed to accomplish a variety of tasks. The research in the field has a history of many decades, but after a diminishing interest in the 1970s, a massive growth started in the early 1980s. Today, Neural Networks can be configured in various arrangements to perform a range of tasks including pattern recognition, data mining, classification, forecasting and process modeling [37]. ANNs are composed of attributes that lead to perfect solutions in applications where we need to learn a linear or nonlinear mapping. Some of these attributes are: learning ability, generalization, parallel processing and error endurance. These attributes would cause the ANNs solve complex problem methods precisely and flexibly [38,39]. ANNs consists of an inter-connection of a number of neurons. There are many varieties of connections under study, however here we will discuss only one type of network which is called the multi layer perceptron (MLP). In this network the data flows forward to the output continuously without any feedback. Fig. 1 shows a typical three-layer feed forward model used for forecasting purposes. The input nodes are the previous lagged observations while the output provides the forecast for the future value. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. The model can be written as:

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-1} + \beta_{0j}\right) + \varepsilon_t \qquad (1)$$

where m is the number of input nodes, n is the number of hidden nodes, f is a sigmoid transfer function such as the logistic: $f(x) = 1/1 + \exp(-x)$. $\{\alpha_j, j=0, 1, \ldots, n\}$ is a vector of weights from the hidden to output nodes and $\{\beta_{ij}, i=1, 2, \ldots, m; j=0, 1, \ldots, n\}$ are weights from the input to hidden nodes. α_0 and β_{0j} are weights of arcs leading from the bias terms which have values always equal to 1. Note that Eq. (1) indicates a linear transfer function is employed in the output node as desired for forecasting problems. The MLP′s most popular learning rule is the error back propagation algorithm. Back Propagation learning is a kind of supervised learning introduced by Werbos [40] and later developed by Rumelhart and McClelland [41]. At the beginning of the learning stage all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input-desired output pattern pairs. Each input–output pair is obtained by the offline processing of historical data. These pairs are used to adjust the weights in the network to minimize the sum squared error (SSE) which measures the difference between the real and the desired values over all output neurons and all learning patterns.

After computing SSE, the back propagation step computes the corrections to be applied to the weights. The ANN models are researched in connection with many power system applications, short-term forecasting being one of the most typical areas. Most of the suggested models use MLP networks [42–45]. The attraction of MLP has been explained by the ability of the network to learn complex relationships between input and output patterns, which would be difficult to model with conventional algorithmic methods.

There are three steps in solving an ANN problem which are (1) training, (2) generalization and (3) implementation. Training is a process that network learns to recognize present pattern from input data set. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units. For this reason each ANN uses a set of training rules that define training method. Generalization or test evaluates network ability in order to extract a feasible solution when the inputs are unknown to network and are not trained to network. We determine how closely the actual output of the network matches the desired output in new situations. In the learning process the values of inter-connection weights are adjusted so that the network produces a better approximation of the desired output. ANNs learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself and its operation can be unpredictable. In this paper the effort is made to identify the best fitted network for the desired model according to the characteristics of the problem and ANN features.

At the present work, we have considered more effective input parameters which impact on renewable energy consumption and also lagged observation is considered. The data is collected for a robust period (about 130 periods) and is further divided to train and test groups. Train data is used to train the MLP models. Test data is used to be compared with actual data (validation). Moreover, the best fitted MLP is identified by the lowest MAPE. In addition, the selected MLP is compared with different regression and fuzzy regression models. Fig. 2 presents the overall description of the model. Fig. 3 presents the ANN pictorial of the proposed model.

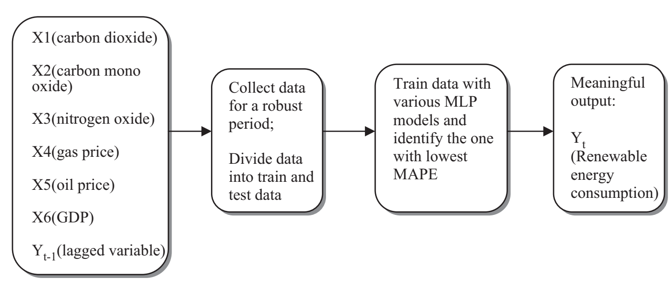

Fig. 2. Description of the ANN model.

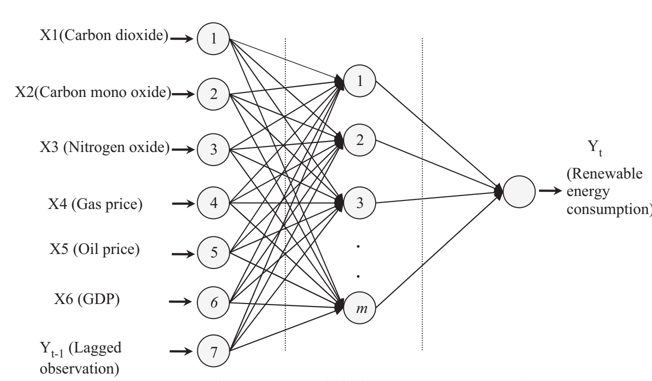

Fig. 3. The integrated ANN-MLP model.

4.1. Error estimation methods

There are four basic error estimation methods which are mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and mean absolute percentage error (MAPE). They can be calculated by the following equations, respectively:

$$\mathrm{MAE} = \frac{\sum_{t=1}^{n} |x_t - x'_t|}{n} \tag{2}$$

$$\mathrm{MSE} = \frac{\sum_{t=1}^{n} (x_t - x'_t)^2}{n} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (x_t - x'_t)^2}{n}} \tag{4}$$

$$\mathrm{MAPE}(\%) = \frac{\sum_{t=1}^{n} |x_t - x'_t / x_t|}{n} \times 100 \tag{5}$$

All methods, except MAPE have scaled output. MAPE method is the most suitable method to estimate the relative error because input data used for the model estimation, preprocessed data and raw data have different scales [9].

5. Experiment: The case study

The proposed model was applied in Iran. Data for these parameters are provided from Institute for International Energy Studies (IIES) in Iran and Energy Information Administration (EIA) website (http://www.eia.doe.gov/emeu/international/contents). The required data was collected monthly for 11 years from 1996 to 2006. We divided these set of data into two groups: the training subset and the test subset. For the training subset related data of 110 periods (months) were considered and used for learning the model and for the test subset relevant data of 20 months were used to test the capability of the model.

5.1. The best structure of ANN

Several MLP networks were generated and tested. The transfer function for the first layer and all hidden layers were sigmoid and for the last one was linear. Back propagation (BP) algorithm is used to adjust the learning procedure.

The results of the five best models and their errors are shown in Table 1. The MAPE results in the last row of Table 1 are derived for the test subset. According to Table 1, the best ANN structure is selected which has 6 neurons in the first hidden layer and 4 neurons in the second hidden layer. This ANN structure is trained with BP learning algorithm.

Table 1
Different MLP specifications and MAPE results.

MLP model number	1	2	3	4	5
Number of neurons in first hidden layer	6	4	4	3	6
Number of neurons in second hidden layer	2	2	0	0	4
Learning method	BP	BP	BP	BP	BP
Relative error (MAPE %)	0.73	0.38	0.20	0.23	**0.08***

6. The results and discussion

In this section, we have proposed an integrated ANN model for forecasting renewable energy consumption in Iran. We claim that this model can be used for predicting renewable energy consumption based on input parameters described in Section 1. For this purpose, several MLP networks were considered and average error of each model was calculated. Finally a MLP network with structure of (7–6–4–1) showed the best accuracy for the estimated values of renewable energy consumption in Iran. In other words, our proposed ANN model for predicting renewable energy consumption in Iran has seven input parameters and six neurons in first hidden layer and four neurons in second hidden layer. The final MLP network shows average error of about 0.08%. The proposed model was applied and the estimated values of the proposed model for test subset were compared respect to actual values. The schematic results for the best iteration of forecasted values for tests are shown in Fig. 4.

6.1. Sensitivity analysis

We divided this set of data into two groups of training and test data sets. For analyzing the sensitivity of the results, different sets of test data are formed. The number of test data is changed from 20 to 50 and in each case, the remaining is used for training of the ANN model. The acquired results for the sensitivity analysis are shown in Table 2.

6.2. Verification and validation

The results of the integrated ANN model are compared respect to fuzzy regression and conventional regression models. There are two main approaches in fuzzy regression model development-fuzzy linear regression (FLR) and fuzzy least-squares regression (FlSR) [46,47]. Fuzzy linear regression was first introduced by Tanaka et al. [48] and its variations suggested by Sakawa and Yano [49,50], Peters [51], and Kim and Bishu [52]. Sakawa and Yano [49,50] also introduced fuzzy data in the formulation. They considered the possibility and necessity conditions for fuzzy equality. The fuzzy least-squares regression (FLSR) was firstly introduced by Diamond [53] and Celmins [54,55]. The developed models of this approach are similar to Savic and Pedrycz [56] and Chang and Lee [57]. The basic Tanaka model assumes a fuzzy linear

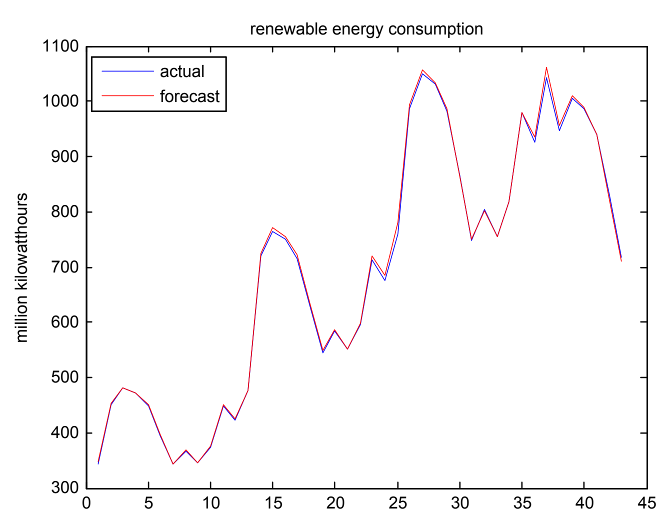

Fig. 4. Comparison of the forecasted consumption with actual consumption.

Table 2
The result of ANN model for different test data sets.

Number of experiment	Number of test	Number of train	MAPE (ANN)%
1	20	110	0.55
2	21	109	0.13
3	22	108	0.1
4	23	107	0.5
5	24	106	0.0036
6	25	105	0.01
7	26	104	0.007
8	27	103	0.49
9	28	102	0.0034
10	29	101	8.2
11	30	100	0.13
12	31	99	0.02
13	32	98	0.0035
14	33	97	2.76
15	34	96	0.59
16	35	95	3.66
17	36	94	0.07
18	37	93	0.037
19	38	92	0.067
20	39	91	0.16
21	40	90	1.097
22	41	89	3.79
23	42	88	1.5
24	43	87	0.05
25	44	86	0.155
26	45	85	0.08
27	46	84	0.062
28	47	83	2.8
29	47	82	0.367
30	49	81	0.075
31	50	80	2.19
		Mean	**0.96**
		The best	**0.0034**

Table 3
The results of different fuzzy regression′s models.

Fuzzy regression model	Parameter of models	MAPE (%)
Tanaka et al. [48]	$H=0.1$	228100
Özelkan [47]	$H=0.9$	**99.5***
Peters [51]	No feasible solution	–

function as shown in Model (6):

$$\tilde{Y}=\tilde{A}_0X_0+\tilde{A}_1X_1,...,\tilde{A}_NX_N=\tilde{A}X \tag{6}$$

where $X=[X_0,\ X_1\ldots\ X_N]^T$ is a vector of independent variables, $\tilde{A}=[\tilde{A}_0,\tilde{A}_1,...,\tilde{A}_N]^T$is a vector of fuzzy coefficients presented in the form of symmetric triangular fuzzy numbers denoted by $\tilde{A}=(\alpha_j,c_j)$. Where α_j is its central value and c_j is the spread value. Thus, Model (6) can be rewritten as Model (7):

$$\tilde{Y}_I=(\alpha_0,c_0)+(\alpha_1,c_1)X_1+\cdots+(\alpha_N,c_N)X_N \tag{7}$$

The above fuzzy regression analysis assumes the crisp input and output data, while the relation between the input and output data is defined by a fuzzy function. By applying the Extension Principle, it derives the membership function of estimated value. Each value of the dependant variable can be estimated as a fuzzy number $\tilde{Y}_i=(Y_i^L,Y_i^{h=1},Y_i^U)$, $i=1, 2\ldots M$, where the lower bound, central value and the upper bound are shown in Model (8):

$$Y_i^l=\sum_{j=0}^{N}(\alpha_j-c_j)x_{ij}$$

$$Y_i^{h=1}=\sum_{j=0}^{N}\alpha_jx$$

$$Y_i^u=\sum_{j=0}^{N}(\alpha_j+c_j)x_{ij} \tag{8}$$

Thus, the proposed model of Tanaka becomes Model (9) as follows:

$$Z=\text{Min}\ \sum_{j=0}^{N}c_j$$

$$\sum_{j=0}^{N}\alpha_jx_{ij}+(1-h)\sum_{j=0}^{N}c_j|x_{ij}|\geq\overline{y}_i+(1-h)\overline{e}_i\quad\forall i=1,2,\ldots,M$$

$$\sum_{j=0}^{N}\alpha_jx_{ij}-(1-h)\sum_{j=0}^{N}c_j|x_{ij}|\leq\overline{y}_i-(1-h)\overline{e}_i\quad\forall i=1,2,\ldots,M$$

$$c_j\geq0,\ a\in R,\ x_{i0}=1,\ 0\leq h\leq1; \tag{9}$$

where the term h is referred to as a measure of goodness of fit or a measure of compatibility between data and a regression model and $\overline{y}_i$ is the center and $\overline{e}_i$ is the spread of the ith collected data. Fuzzy least-squares regression (FLSR) has had very few criticisms because of its similarity to traditional least-squares regression. However, FLSR is sensitive to outliers and it should be used only when enough data are available which results in losing one of the advantages of the fuzzy regression. Özelkan and Duckstein [47] developed a bi-objective fuzzy regression model (BOFR) which is capable of solving the problems of fuzzy linear regression (FLR), mentioned above, especially the problem of data outliers as shown by Model (10).

Table 4
Coefficients of regression models.

	Input variables						**Lagged variable**	**Constant value**
	X_1	X_2	X_3	X_4	X_5	X_6	Y_{t-1}	
Fuzzy regression	0	0	0.0004	0	0	0.97	0	0
Linear regression (I)	0.8	0	0	−14.5	0	0.1	84.4	−4109.6

Table 5
The results of different regression′s models.

Regression′s models	MAPE (%)
Model (I)	**8.90***
Model (II)	11.21
Model (III)	26.01
Model (IV)	11.20
Model (V)	10.31
Model (VI)	9.20

Table 6
Comparison of the best acquired results.

	Conventional regression	Fuzzy regression	Proposed ANN
The best MAPE (%)	8.90	99.5	0.0034

Table 7
Comparison of the proposed ANN with other approaches.

Method	Multiple inputs	Multiple outputs	Data complexity and non-linearity	Intelligent modeling and forecasting	Learning module	High precision and reliability	Flexibility
The proposed approach	✓	✓	✓	✓	✓	✓	✓
Fuzzy regression	✓						✓
Linear regression	✓						
Fuzzy inference systems	✓						✓
Genetic algorithm	✓		✓		✓		
Decision tree	✓		✓		✓	✓	

6.3. *Min-dominated {V, E^p}*

Subject to:

$$\left(\sum_{j=0}^{N}\alpha_j x_{ij} - (1-h)\sum_{j=0}^{N}c_j|x_{ij}|\right) - (\overline{y}_i - (1-h)\overline{e}_i) \le \varepsilon_{L,i}$$

$$(\overline{y}_i + (1-h)\overline{e}_i) - \left(\sum_{j=0}^{N}\alpha_j x_{ij} + (1-h)\sum_{j=0}^{N}c_j|x_{ij}|\right) \le \varepsilon_{R,i}$$

$$\varepsilon_{L,i}, \varepsilon_{R,i} \ge 0 \forall i = 1, 2, ..., M. \tag{10}$$

where V denotes the vagueness measure defined as the spread of the prediction to be minimized and $E^p$is the deviation from outliers which are brought in Model (11) and $\varepsilon_{l,i}, \varepsilon_{R,i}$are relaxation variables.$0<p<\infty$ is the compensation level. The expression "min-dominated" indicates the non-inferior solution-finding process.

$$V = \sum_{i=1}^{M}((\sum_{j=0}^{N}\alpha_j x_{ij} + (1-h)\sum_{j=0}^{N}c_j|x_{ij}|) - (\sum_{j=0}^{N}\alpha_j x_{ij} - (1-h)\sum_{j=0}^{N}c_j|x_{ij}|))$$

$$E^p = \sum_{i=1}^{M}(\varepsilon_{L,i}^p + \varepsilon_{R,i}^p) \tag{11}$$

Moreover, they proved that fuzzy linear regression (FLR) models of Tanaka et al. [48], Tanaka [58], Peters [51] and classic crisp (non-fuzzy) regression model are specific cases of their model. Although having several advantages compared to other fuzzy linear regression (FLR) models, the Özelkan′s model still has some drawbacks, such as the central tendency property does not exist fully and explicitly in the model.

The results of different fuzzy regression models have been shown in Table 3. As it is shown in Table 3, the best result for fuzzy regression models is resulted by using the Özelkan′s model. Also, the Tanaka′s model could not be used for forecasting of renewable energy consumption in Iran. To validate the proposed ANN in an efficient way, we use different regression models for estimation and forecasting of renewable energy consumption. Table 4 shows the coefficients of regression model (I) and fuzzy regression model of Özelkan [47]. The results of regression models have been illustrated in Table 5. As depicted in Table 5, the best result of regression models is resulted by using the regression model (I). The used regression models have been shown in Appendix A.

It can be concluded from the acquired results that linear assumption could not be considered for the relationship between inputs and output of the model. Also, the MAPE value of fuzzy regression models is not acceptable for prediction of renewable energy consumption. As it is shown in Table 6, the ANN model is superior to regression and fuzzy regression models. Also, regression model (I) is better than fuzzy regression model for forecasting renewable energy.

Table 7 compares the most important features of the proposed integrated ANN with other well-known approaches applied in optimization and forecasting. Clearly, the approach of this study bypasses previous studies with respect to several distinct features.

7. Conclusion

Considering the limited energy resources and harmful effects of fossil fuels, utilization of renewable energy has an important role in sustainable development of a country. Planning for utilization of renewable energy resources is needed to an efficient tool for prediction of renewable energy consumption. Artificial Neural Networks have proved their capabilities as a precious prediction tool. In this paper, we have used an innovative ANN model for prediction of renewable energy consumption. For this model a number of effective input parameters were introduced and applied in the structure of ANN model. Considering the literature, these parameters are the most effective parameters which impact on renewable energy consumption. These factors include carbon dioxide emission, nitrogen oxide emission, carbon mono oxide emission, gas price, oil price and GDP. Also one lagged observation was considered as input parameter. To show the applicability and superiority of the proposed framework actual data for described input parameters for 130 months was used. MLP network was used and applied with seven input variables. After tuning, the optimum number of neurons is determined in various layers. The acquired results of the proposed ANN model were compared respect to different regression and fuzzy regression models. The proposed ANN model indicated its superiority in achieving the lowest MAPE compared to other common approaches used for forecasting. It can be concluded that the proposed ANN model can be effectively used for forecasting renewable energy consumption. Also, the proposed ANN model can be very beneficial for improving and optimizing renewable energy consumption in some of remote or rural locations with no available devices for measurement of renewable energy consumption.

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Appendix A. Regression models

Model (I):
$$y = \alpha_0 + \sum_{i=1}^{7}\alpha_i X_i \tag{A.1}$$

Model (II):
$$\ln y = \alpha_0 + \sum_{i=1}^{7}\alpha_i(\ln X_i) \tag{A.2}$$

Model (III):
$$y = \alpha_0 + \sum_{i=1}^{7}\alpha_i X_i + \sum_{i=1}^{7}\beta_i X_i^2 \tag{A.3}$$

Model (IV):

$$\ln y = \alpha_0 + \sum_{i=1}^{7} \alpha_i (\ln X_i) + \sum_{i=1}^{7} \beta_i (\ln X_i^2) \tag{A.4}$$

Model (V):

$$y = \alpha_0 + \sum_{i=1}^{7} \alpha_i X_i + \sum_{i=1}^{7} \beta_i X_i^2 + \sum_i^7 \sum_{i \neq j}^{7} \gamma_{ij} X_i X_j \tag{A.5}$$

Model (VI):

$$\ln y = \alpha_0 + \sum_{i=1}^{7} \alpha_i (\ln X_i) + \sum_{i=1}^{7} \beta_i (\ln X_i^2) + \sum_i^7 \sum_{i \neq j}^{7} \gamma_{ij} (\ln X_i X_j) \tag{A.6}$$

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